

LAB Logbook

Lab 1

Lab Logbook Requirement:

1) Create a vector using *np.arange*.

Determine the number of the vector elements using the following method: Take the last two digits from your SID. It should be from 00 to 99. If this number is 10 or more, it becomes the required number of the vector elements. If it is less than 10, add 100 to your number.

For example, if your SID is 2287467, and the last two digits are 67, which is greater than 10. The required number is 67. If your SID is 2287407, and the last two digits are 07, which is less than 10. The required number is 107.

Then,

2. Change matrix a to 2-d array with 1 row. Print the array. You should have the two sets of brackets for a 2-d array with one row.
3. Save it in another array. Print the array.
4. Check the shape attribute value.
5. Add the code and result to your Lab Logbook

NOTE: DON'T FORGET TO SAVE AND BACK UP YOUR COMPLETED JUPYTER NOTEBOOK AND LAB LOGBOOK ON GITHUB OR ONEDRIVE.

```
In [69]: SID = 2285050
```

```
In [72]: number_of_vector_elements = 50
vector = np.arange(number_of_vector_elements)
print("Vector: ", vector)
```

```
Vector: [ 0  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23
24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47
48 49]
```

```
In [73]: _2d_array = vector.reshape(1, -1)
print("2D array with one row: ", _2d_array)
```

```
2D array with one row: [[ 0  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23
24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47
48 49]]
```

```
In [74]: another_array = _2d_array.copy()
print("Another array: ", another_array)
```

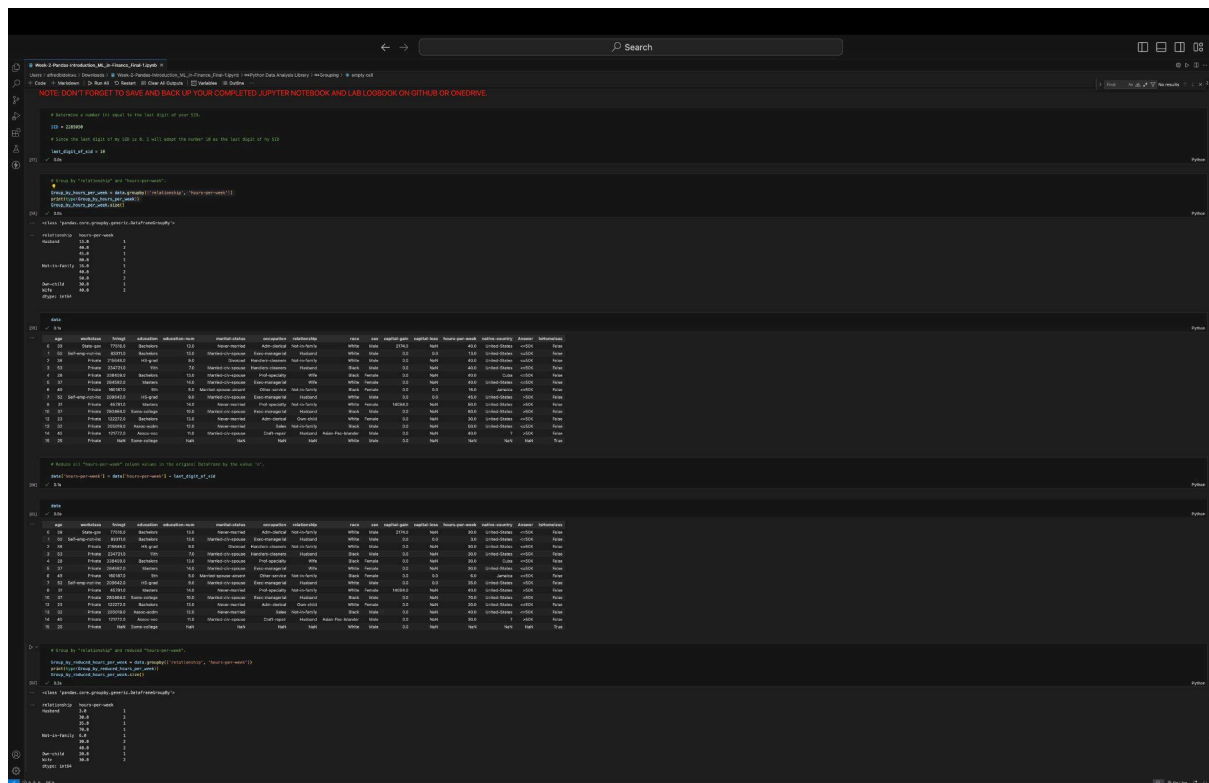
```
Another array: [[ 0  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23
24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47
48 49]]
```

```
In [75]: shape_value = another_array.shape
print("Shape: ", shape_value)
```

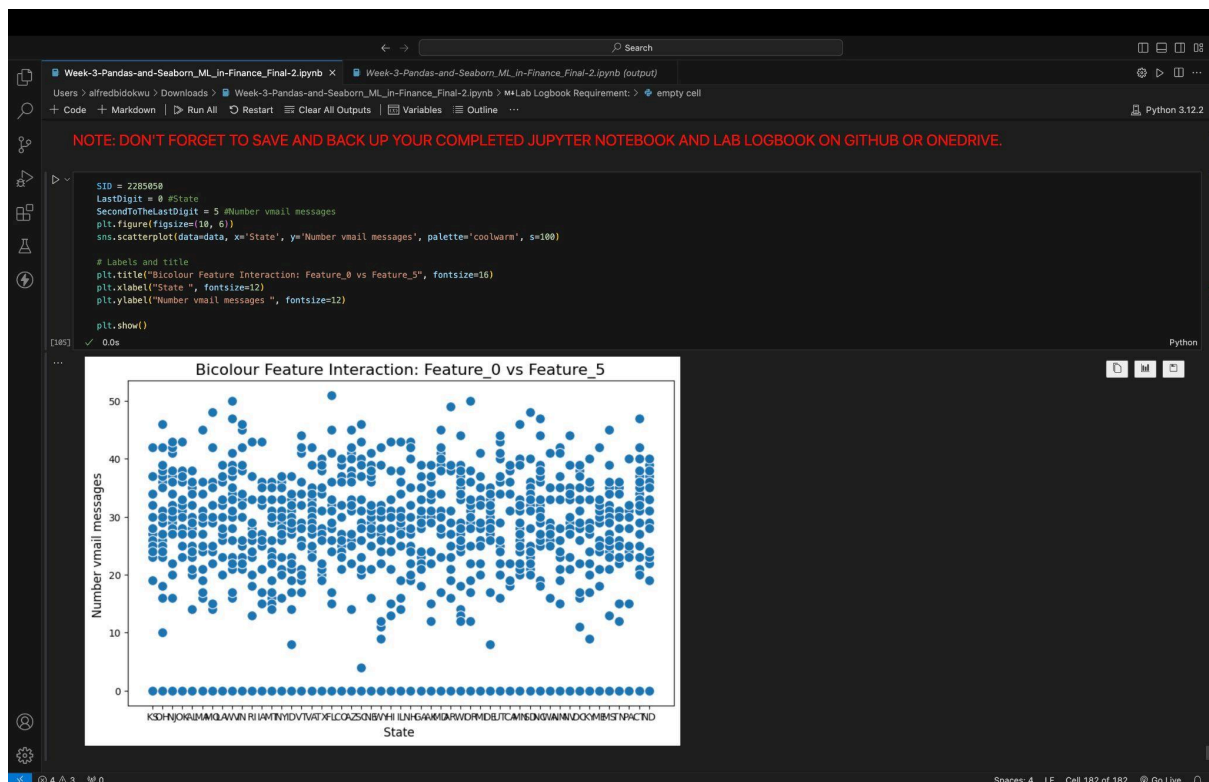
```
Shape: (1, 50)
```

```
In [ ]:
```

Lab 2



Lab 3



Lab 4

```
Week 4 MLP_SSP_ML_In-Finance_Final-1gynb
layers > attach(browser) > Downloadable > Week 4-MLP_SSP_ML_In-Finance_Final-1.gynb > ML Lab Logbook Requirement > ML Model evaluation > ML MAE in the practical: Mean absolute error: 0.03778
Code > Markdown > Run All > Restart > Clear All Outputs > Variables > Outline
Model: "sequential_2"

Layer (type)                Output Shape                Param #
dense_8 (Dense)              (None, 10)                  71,498
dense_9 (Dense)               (None, 10)                  1,175
dense_10 (Dense)              (None, 1)                   26
Total params: 72,673 (182.93 KB)
Trainable params: 72,673 (182.93 KB)
Non-trainable params: 0 (0.00 KB)
None

# Compile the model
model_custom.compile(optimizer="adam", loss="mse", metrics=["mae"])

# Train the model
history_custom = model_custom.fit(x_train, y_train, batch_size=10, epochs=10, validation_split=0.2, verbose=1)

Epoch 1/10
2648/2648 --- 1s 362us/step - loss: 0.8620 - mae: 0.8219 - val_loss: 0.8056 - val_mae: 0.8073
Epoch 2/10
2648/2648 --- 1s 275us/step - loss: 1.2434e-04 - mae: 0.8885 - val_loss: 0.8023 - val_mae: 0.8428
Epoch 3/10
2648/2648 --- 1s 275us/step - loss: 9.7513e-05 - mae: 0.8076 - val_loss: 0.8028 - val_mae: 0.8489
Epoch 4/10
2648/2648 --- 1s 275us/step - loss: 6.8895e-05 - mae: 0.8063 - val_loss: 0.8011 - val_mae: 0.8294
Epoch 5/10
2648/2648 --- 1s 285us/step - loss: 6.4893e-05 - mae: 0.8068 - val_loss: 0.8016 - val_mae: 0.8408
Epoch 6/10
2648/2648 --- 1s 287us/step - loss: 5.8711e-05 - mae: 0.8057 - val_loss: 0.8013 - val_mae: 0.8333
Epoch 7/10
2648/2648 --- 1s 284us/step - loss: 5.7057e-05 - mae: 0.8056 - val_loss: 3.9831e-04 - val_mae: 0.8181
Epoch 8/10
2648/2648 --- 1s 298us/step - loss: 4.7666e-05 - mae: 0.8053 - val_loss: 3.0980e-04 - val_mae: 0.8144
Epoch 9/10
2648/2648 --- 1s 274us/step - loss: 4.9788e-05 - mae: 0.8053 - val_loss: 2.8684e-04 - val_mae: 0.8116
Epoch 10/10
2648/2648 --- 1s 279us/step - loss: 4.7215e-05 - mae: 0.8058 - val_loss: 3.4380e-04 - val_mae: 0.8152

Model evaluation

# Evaluate the model
mse_custom, mae_custom = model_custom.evaluate(x_test, y_test, verbose=0)

# Output the results
print("Custom Model - Mean Absolute Error (MAE): %.3f" % mae_custom)
print("Custom Model - Mean Squared Error (MSE): %.3f" % mse_custom)

Custom Model - Mean Absolute Error (MAE): 0.84276
Custom Model - Mean Squared Error (MSE): 0.86219

MAE in the practical: Mean absolute error: 0.83778
MAE of my own model: Custom Model - Mean Absolute Error (MAE): 0.84276

The MAE of my own model is 0.84276 which is slightly higher than the MAE of the practical session which was 0.83778

A lower MAE is better and more preferable because a lower MAE means that, on average, the model's predictions are closer to the true values, indicating a more accurate model.
```

Lab 5

```
Recommended code is provided for safe code browsing. Trust this window to enable all features.
Week 5-CH4_FML460_ML_In-Finance_Final-1gynb
layers > attach(browser) > Downloadable > Week 5-CH4_FML460_ML_In-Finance_Final-1gynb > ML Lab Logbook Requirement > ML Model evaluation > ML MAE in the practical: Mean absolute error: 0.03778
Code > Markdown > Run All > Restart > Clear All Outputs > Variables > Outline
Model: "sequential_2"

1. Load the data and preprocess it.
2. Split the data into training and testing sets.
3. Compile the model.
4. Train your CNN with the same datasets and architectures. Record the test MAE. Compare your MAE with the MAE of the CNN in the practical session.
5. Please only add a print screen of your CNN architecture, loss model, and the resulting MAE to your Lab Logbook.

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My ID = 2786030
Identify Z and Y
Z is the second-to-last digit of my ID, which is 5. Y is the last digit of my ID, which is 0.
Apply the Formula:
According to the condition: Z + Y, P, Z = 0
10 + 5 + 0 = 15 and 15 is not 0
10, P, Z = 5 + 0
Since none of the formulas explicitly said what to do if Y is 0 and Z is not 0, we apply the formula that says
Z + Y, P, Z and Y are not 0
Therefore 0 + 5 = 5
New number of epochs = 5

model = keras.Sequential([
    keras.layers.Dense(10, input_shape=(10,)),
    keras.layers.Dense(10),
    keras.layers.Dense(10),
    keras.layers.Dense(10),
    keras.layers.Dense(10),
    keras.layers.Dense(10),
    keras.layers.Dense(10),
    keras.layers.Dense(10),
    keras.layers.Dense(10),
    keras.layers.Dense(10)
])

print(model.summary())

model.compile(optimizer="adam", loss="mse", metrics=["mae"])

history = model.fit(x_train, y_train, batch_size=10, epochs=5, validation_split=0.2, verbose=1)

Epoch 1/5
1024/1024 --- 1s 261us/step - loss: 0.8076 - mae: 0.8102 - val_loss: 0.7533e-04 - val_mae: 0.8281
Epoch 2/5
1024/1024 --- 1s 261us/step - loss: 7.4853e-04 - mae: 0.8108 - val_loss: 0.6430e-04 - val_mae: 0.8192
Epoch 3/5
1024/1024 --- 1s 261us/step - loss: 7.2613e-04 - mae: 0.8103 - val_loss: 0.5880e-04 - val_mae: 0.8191
Epoch 4/5
1024/1024 --- 1s 261us/step - loss: 7.2613e-04 - mae: 0.8108 - val_loss: 0.6000e-04 - val_mae: 0.8201
Epoch 5/5
1024/1024 --- 1s 261us/step - loss: 0.3890e-04 - mae: 0.8173 - val_loss: 0.6880e-04 - val_mae: 0.8153

mse, mae = model.evaluate(x_test, y_test, verbose=0)
print("Mean absolute error: %.3f" % mae)

MAE: 0.8153
Mean absolute error: 0.8153

The new mean absolute error is 0.8153, while the mean absolute error from the practical was 0.83778. The new mean absolute error is lower than what we had in the practical, therefore it means that the new model's predictions have a slightly lesser error than the model from the practical session.
NB: The lower the MAE the better the performance of the model, since the mean absolute error measures the average of the errors (distance from the true value).
```

Lab 6

Lab 7

Lab 8

Lab 9

Lab 10

Lab 11

Lab 12